Sensitivity analysis of climate change risk assessment

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Contents

Chapter 1

Introduction

1.1 Conceptual overview

Climate change is shaping ecosystems and human activities and is becoming a central topic of discussion across all fields.[40, 41] Effects of climate change have different severity, often changing with time and with the evolution of contexts they occur.[20] These impacts may depend also on the spatial scale of the systems affected.[16]

The knowledge of present and future impacts of climate change becomes essential to reduce adverse outcomes, as well as to leverage potential benefits. Even more relevant is the concept of risk which moves the focus from the impacts to their potential occurrence, broadening the possibilities for related studies and actions. In fact, an increasing number of organisations are incorporating climate change risk assessments (CCRAs) into their decision processes.[8] A definition of risk assessment is given by Intergovernmental Panel on Climate Change (IPCC) as *The qualitative and/or quantitative scientific estimation of risks.*, from [34, p. 2246], and CCRA is its restriction to climate-related risks.[1] Other authorities employ similar definitions of risk assessment and remark its usefulness.[31, 53]

More generally, a risk assessment is essential part of the process of risk management, which uses the assessed information to reduce risk through the application of, e.g. policies, strategies, adaptation plans.[3] The objectives of risk management are defined in the broad field of disaster risk reduction (DRR).[45]

CCRA combines DRR practices and concepts with climate information.[24, 23] Some insights on the synergy between the fields of DRR and climate change adaptation are exposed in [23, pp. 469–471].

Credible climate information are refined by scientific data and in cooper-

[1]Terms *climate change risk assessment* and *climate risk assessment* are used equivalently in literature (cf. [24, p. 11] and [49, p. 20], also [33]). In this document the former is used, to highlight the focus on risks arising from climate change.

ation with users and stakeholders. They are the product of climate services, being the provision of climate-related data and information to assist decision-making.[30]. An overview of the evolving field of climate services is available in [16, pp. 1431–1433] and in [42, pp. 1862–1869].

Various regulations, standards and guidelines for CCRA are available, but very few specify in detail the methodology to follow.[33] Methodologies differ by various means, e.g. the steps required to gather preliminar information on impacts and risks, the analysis of the system exposed, the evaluation of risk and its components, the presentation of outcomes (cf. [31, 20, 49, 6, 11], also see [33, pp. 10–11] and [24, p. 9]). This variety hinders the comparison of CCRA outcomes, diminishing their credibility and interoperability.[26]

A single methodology may be chosen to perform the CCRA, but the issue presents once again since the methodology may not define operational details, e.g. functions and procedures involved. Implementation details are left to the authors of the CCRA, who base the choice on their experience and on scientific literature, according to the principles of climate services. To evaluate the dependence of risk on the functional representation of its components is the objective of this work.

The methodology of CCRA applied in the present work follows [49] and its upgrade [24]. The latter should be read in parallel with the former and supersedes outdated concepts.

1.1.1 Climate risk

Before stating the objective of the present study, first it is convenient to introduce a proper terminology. Definitions by International Organization for Standardization (ISO) are used for their concision. When some terms are not available, they are taken from IPCC. Both sources have similar definitions for the same terms.

Risk is a general term which can be tailored to different contexts and applications as a measure of uncertain consequences on a system of interest.[2] A system is very broadly any concrete or abstract entity which can be affected by risk.

Example

Some possible systems which can be exposed to risks are any physical system, communities of people, an idea.

A paradigmatic example is the financial sector, where the concept of risk is widely known and is connected directly to economic value and the concept

[2]Without delving into Philosophy, a source of change is needed to have consequences and it is specified by the definitions in use.

of portfolio, to the point that financial risk management can be considered a research field itself.[10] Examples on how other fields implement the concept are elaborated in [24, p. 14] and in [43].

In this work the risk related to climate change is: *effect of uncertainty*, from [31].[3] IPCC proposes a similar definition, expanding on the entities involved (e.g. the possible systems) and the contexts in which the term is used, but focusing only on negative effects: *The potential for adverse consequences for human or ecological systems, recognizing the diversity of values and objectives associated with such systems. In the context of climate change, risks can arise from potential impacts of climate change as well as human responses to climate change. Relevant adverse consequences include those on lives, livelihoods, health and well-being, economic, social and cultural assets and investments, infrastructure, services (including ecosystem services), ecosystems and species. [...]*, from [34, p. 2246]. An important aspect of climate risk is that it originates from both impact of climate change, i.e. *effect on natural and human systems (3.3)*, from [31], and any response to it, i.e. action enact to mitigate the effects of climate change or adapt to it. It is not common to see responses integrated into risk assessment, as exposed by [47, p. 492], and for the purposes of the present study they are neglected. From this perspective, two types of climate risk are studied in CCRAs: transition risk and physical risk. The former regards impacts on finance, economy and society caused by decarbonisation and transitioning to a sustainable economy, the latter is the risk related to the realisation of physical hazards. Both types of risk are assessed by organisations and financial institutions,[9, 48] however only physical risks are considered in this study. Henceforth, terms climate risk and risk are used interchangeably and both refer to climate-related physical risks.

To make the assessment easily extensible and modular, risk is defined as the result of the interaction of three elements, i.e. its determinants, namely hazard, exposure and vulnerability. Response is considered the fourth determinant of risk, when the adopted methodology includes it in the assessment. Definitions of determinants were introduced in [23, pp. 69–70] and offer a change of direction from previous methodologies centered on the concept of vulnerability of the system instead of the overall risk (cf. [49] and [24]).

The hazard is defined by ISO as *potential source of harm*, from [31] and is elaborated further by IPCC on which subjects it applies to. No particular reference is made to the climate system in the definitions, hence IPCC provides the more specific term climatic impact-driver (CID) in [34, p. 2224] to address to climate-related physical phenomena and with a neutral connotation (cf. [43, p. 10] or [42, pp. 1871–1872]). In the following the term hazard is used to address to climate-related hazards for brevity.

[3] Note that this definition is not specific to climate risk since no reference to climate is made.

The exposure of a system is determined by *presence of people, livelihoods, species or ecosystems, environmental functions, services, resources, infrastructure, or economic, social or cultural assets in places and settings that could be affected*, from [31].

The vulnerability of a system is *propensity or predisposition to be adversely affected*, from [31]. Properties of the system which determine its vulnerability may be classified further in sensitivity, i.e. *degree to which a system (3.3) or species is affected, either adversely or beneficially, by climate (3.4) variability or change*, from [31], and adaptive capacity, i.e. *ability of systems (3.3), institutions, humans, and other organisms to adjust to potential damage, to take advantage of opportunities, or to respond to consequences*, from [31]. This classification in general helps the analysis of the system and the identification of responses, e.g. adaptation measures may increase the adaptive capacity of some elements of the system.

Each determinant may be viewed as a collection of elements, which are of different nature depending on the determinant they belong to, but are addressed generically as drivers.[4] CIDs with negative impacts are effectively drivers within the hazard determinant which are related to the climate system. Hazard drivers used in the present work are selected from the taxonomy provided by European Union for CCRA, to have a well-known and authoritative reference in the field.[11, p. 177] Physical elements of the system may be effectively considered as drivers of exposure.[5]

Example

A tropical storm is a driver within the hazard determinant,[24, p. 15] income is a driver within the vulnerability determinant,[47, p. 493] airport structures (e.g. runways, aprons, terminals) in an airport (i.e. the system) are drivers within the exposure determinant.[14, p. 551] More examples are available in the references.

The concept of driver of risk is borrowed from [47] to allow a smooth extension to methodologies where risk is the result of complex interactions within and across determinants. In section 1.1.2 this topic is described further.

For a quantitative CCRA, numerical values must be associated to drivers. These values are called indicators and defined by ISO as: *quantitative, qualitative or binary variable that can be measured or described, in response to a defined criterion*, from [31].[6] There can be more than one way to describe

[4]When this terminology is not applied, it is common to refer to drivers with the name of the determinants they belong to, e.g. drivers within the vulnerability determinant are simply called vulnerabilities.

[5]In literature different terms are used to refer to drivers within the exposure, e.g. *assets* or *exposed sample* in [14].

[6]The definition by IPCC is not as general because focuses only on the climate system

numerically the same driver, hence the choice is not unique and the resulting risk may be affected by it.

Example

A drought is defined in general by IPCC as *An exceptional period of water shortage for existing ecosystems and the human population (due to low rainfall, high temperature, and/or wind)*, from [34, p. 2226]. Drought is a driver of risk and is a physical phenomena related to climate, hence it belongs to the hazard determinant.
Many indicators of drought are used, e.g. consecutive number of dry days, temperature, indicators combining temperature,precipitation and evotranspiration. See [23, pp. 167–169] for further examples and references; note that the term *index* is used in place of indicator.

In the following, the term indicator written alone refers to an indicator of a driver within the hazard determinant, to relax the lenghty wording. For the other determinants the full qualification is used.

Having introduced the definitions above, the various components of risk can be arranged as in figure 1.1. It sums up the relation between the various components, highlightning the fact that risk depends on drivers from three independent categories and are quantified possibly in multiple ways.

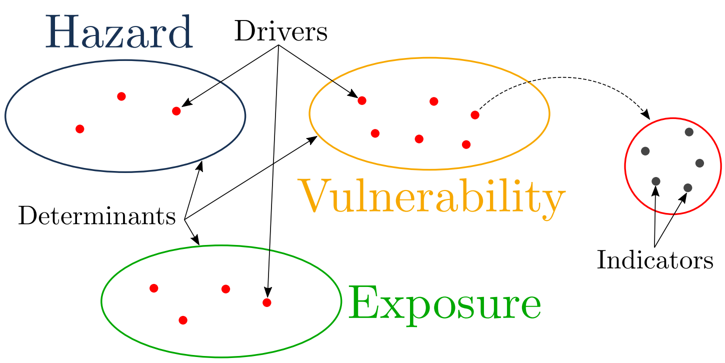


Figure 1.1: A possibile representation of the components of climate risk. Climate hazards can affect exposed and vulnerable elements of the system and determine a risk for it. Collectively these factors are called drivers and can grouped in the three independent determinants of risk: hazard, exposure and vulnerability. To provide quantitative results, each driver is described by numerical values, i.e. the indicators, each providing a different possible description or measure of the same driver.

1.1.2 Complex risk

Unlike other types of risk assessment, e.g. probabilistic risk assessment, CCRA focuses on interactions between drivers instead of estimating their

and there is no specific term for the same concept applied to the other determinants.

likelihood.[24, pp. 20–21] However, it is common to study each determinant in isolation. Instead, an integrated risk assessment which is able to relate drivers within and across determinants would be able to describe the overall risk more accurately.[4, pp. 145–147]

Interacting elements are not considered mainly because a proper formalisation of the interactions is difficult and rarely clear. In [47] the list of complex risk adopted by IPCC in Sixth Assessment Report (AR6) is extended, to allow more granularity in the assessment, and three categories of complex risk are proposed. The objective is to build a framework which helps to address to complex interactions more easily, thus helping their adoption in CCRAs. Response is included in the determinants, e.g. to introduce negative effects on vulnerability due to maladaptation. Depending on what is the origin of risk, the categories are:[47, p. 493]

1. interacting drivers within the same determinant;
2. interacting drivers across different determinants;
3. interacting risks.

In general, category 1 is considered as long as the methodology admits an aggregation of drivers to obtain each determinant.

Example

Flood risk in a geographical area is assessed. First, only artificial constructions are considered as system. The change in time of precipitation and temperature, i.e. drivers of risk within the hazard determinant, are aggregated to give a measure of the hazard. With this value and the analogous values of the other determinants, a category 1 risk can be evaluated, which measures the interaction of its determinants only defined by the methodology and lacking a particular meaning.
A collateral change in soil properties due to precipitation and temperature is added to the study. This results in a decrease of soil adaptive capacity, hence an increase of the vulnerability of buildings in that area. This interaction belongs to category 2.
A second iteration of the CCRA moves the focus to human activities in the area under study. When the corrispondent risk is evaluated, it can be merged with the risk value found previously to summarise the overall flood risk, which becomes a category 3 complex risk.

All three categories of complex risk may be found in the methodology (see section 2.3 for details), but in the present work only category 1 is considered, as there is no particular relation between drivers within different determinants, except for the aggregation into the final risk value. Nevertheless, extending the current study by introducing complexity throught the other categories may be interesting to test the robustness of the results.

From a mathematical point of view, complex interactions between drivers translate to mathematical functions which relate indicators. They may be treated as additional indicators to consider in the aggregation of determinants.[38, pp. 39–40] In the chosen methodology, no specific interaction is considered between drivers across determinants. This translates into linear relations between indicators when they are aggregated.

1.1.3 Problem statement

The objective of this work is to show how the risk evaluated following a given methodology depends on the choice of indicators. In particular, the study is restricted to indicators of hazard and their definitions are modified by varying the parameters they depend on.

Technically this study resembles a sensitivity analysis (SA): the effects on the outcome of a system by varying its input factors are assessed and attributed to specific input factors.[15, pp. 627–632] In this case the system is the CCRA and the methodology which implements it, its outcome is the risk value and the input factors are the parameters. More in detail, this work adopts a global approach to SA, since the space of all possible parameters, or a significative subset of it, is explored. This is essential for a significative SA, because indicators are generally non-linear functions of their parameters, hence the relation of the system on the input space is highly non linear.[44, pp. 31–32]

A SA is normally preceded by an uncertainty analysis (UA), which quantifies the uncertainty on the output of the system by exploring the statistical properties of the system and its inputs.[44, pp. 29–30] The present study does not employ strictly an UA, because probability distributions of parameters and their uncertainties are not considered explicitly, a non-parametric space-filling approach is adopted instead. An estimation of uncertainties would be possible by employing multiple instances of the input space (e.g. bootstrapping, Monte Carlo methods). Additionally, uncertainties on climate data are considered only for projections, where a model ensemble is employed.

Results from this work highlight the importance of indicators parameters in a CCRA. The methods may be useful to authors of CCRAs to address the arbitrariness of parameters selection and to support the outcomes of the assessment. In this regard, the present study may found an application in climate services.

1.2 Structure of the document

Each section of the document treats a different aspect of the analysis. A general understanding of the concept of risk and the associated terms are useful to frame the problem, they are presented in section 1.1. Given the relevance of data, various sections are dedicated to them. Climate datasets and system-dependent data are described in section 2.1 and **??**, respectively, along with any elaboration applied. Indicators are described mathematically in section 2.2, while the methodology of CCRA is presented in section 2.3. The methodology is then applied to two case studies in section **??**, where system-specific data and results are analysed and the actual SA is performed. In section **??** the effectiveness of the methods is assessed. Finally in section **??** the final considerations on the study and its applicability are summarised.

Chapter 2

Methods

2.1 Climate data

Climate is a complex system, composed by many elements which interact in non-trivial (i.e. non-linear) ways. Therefore, to have a satisfying description of climate, many variables are needed. Climate data are data which can be used to provide a direct or indirect description of climate,[1] e.g. in situ observations, measures from remote sensing or weather stations, outputs from numerical models.[46, p. 1537] The complexity of climate reflects on the complexity in structure of climate data, e.g. they can be represented as multidimensional objects and collected in climate datasets. This affects also their availability and other properties,[22] therefore climate data can be regarded as big data.

To identify a subset of variables which efficiently describe the climate, the concept of essential climate variable (ECV) is defined.[5] The updated list of ECVs and their requirements are mantained by the World Meteorological Organization (WMO) in [2, pp. 14–17]. Climate data necessary for this study are among the present ECVs. In this section they are characterised mathematically, while the actual data are shown in section **??**.

In the following, a generic ECV T can be represented mathematically as a scalar function

$$T : S_{\text{lat}} \times S_{\text{lon}} \times S_{\text{time}} \to \mathbb{R} \tag{2.1}$$

where S_{lat}, S_{lon} and S_{time} are domains of latitude, longitude and time dimensions, respectively.[2] Latitude and longitude are the only spatial dimensions considered, because elevation is specific to each ECV. In the following, when

[1] A note on nomenclature: the adjective *climatological* is used in some sources instead of *climate* to address to climate data. They are equivalent, but the latter is preferred in this work because it replicates the alternative term for normal specified by [1, p. 1].

[2] In contexts related to Machine Learning (ML) these objects are called tensors. Since they may not satisfy the mathematical definition of a tensor, in particular the map may not be multilinear and the numerical sets may not be vector spaces, no reference to such objects is made in this work.

spatial dimensions are mentioned, they refer to the horiziontal dimensions of latitude and longitude. Every numerical value is equipped with proper units of measurement, to represent physical quantities correctly. As a consequence, the codomain in equation (2.1) is partially wrong: with an abuse of notation, it represents only the magnitude of the ECV and does not consider the unit of measurement. This is a small exception to simplify the notation and in the remainder of this document units of measurement are always addressed explicitly.

A more practical representation of T is a multidimensional array, where values in the domain are coordinates associated to each dimension and each entry of the array is the result of T evaluated on those coordinates. Figure 2.1 shows this representation visually. In the following, this representation is

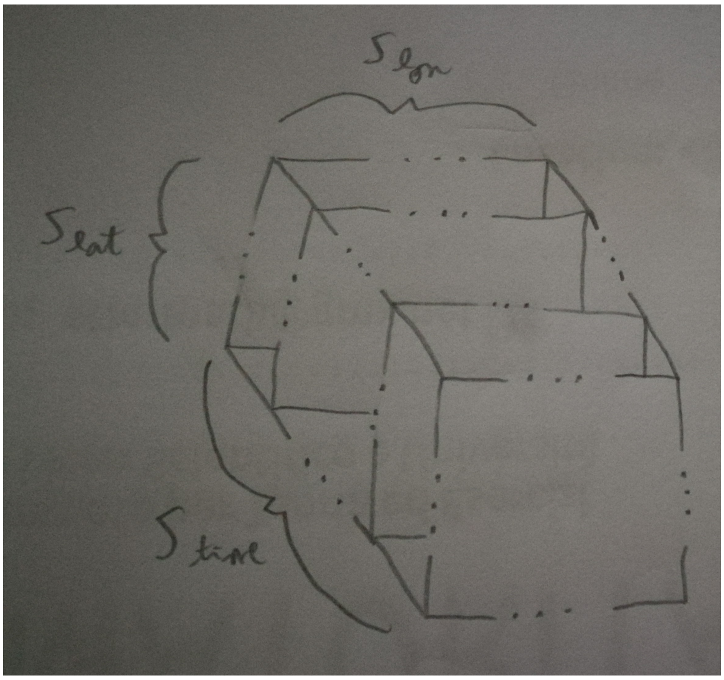


Figure 2.1: Representation of a generic ECV as multidimensional array.

used to simplify the discussion and same ECV symbol is used both for the function and the multidimensional array.

Example

Near-Surface Air Temperature, symbol tas, is available for some coordinates $S_{\text{lat}} \times S_{\text{lon}}$ and timestamps S_{time}. It can be seen as the scalar function in equation (2.1), which associates each value in set $S_{\text{lat}} \times S_{\text{lon}} \times S_{\text{time}}$ to a scalar value with unit K, or it can be represented as the multidimensional array in figure 2.1, where each entry is function (2.1) evaluated at the corresponding coordinates.

As a visual aid when generic symbols are used, capital letters represent both functions and multidimensional arrays, the former being followed by the arguments in parentheses when there is an explicit reference to their values. Instead, lowercase letters are used for functions and values which are one dimensional.

2.1.1 Climate normals

The temporal evolution of climate is described by climate data which can be represented as time series. To quantify changes in the state of climate it is useful to define a reference period and climate data related to it.

The concept of climate normal is introduced for this purpose, the WMO defines it as: *period averages computed for a uniform and relatively long period comprising at least three consecutive ten-year periods*, from [1, p. 2]. Terms Period average and average apply to monthly values of climate data, see definitions and how normals are evaluated in [1, pp. 5–6]. However, the mean of values with other temporal domains may also be useful (e.g. multimonth normals, normal for each day of year of the wind speed at a given location), in the following anomalies are characterised clearly. To quantify changes in the state of climate, anomalies are used, which are *The deviation of a variable from its value averaged over a reference period.*, from [34, p. 2218]. The avarage value for anomalies is usually normal.

In this work the reference period is identified by the symbol $S_{\text{time}}|_{\text{clim}}$ and it is a period of 30 years starting on 1st January of a year ending with the digit 1. This specification satisfies the definition of averaging period for climate normals. Instead, the boundaries are specific to the case study. They are chosen such that the reference period precedes the start of the formation of the system. This arbitrary criterion is chosen to compensate the natural deteriotation of materials, with artifical buildings in mind. In fact, the methodology implicitly assumes that exposure and vulnerability values are either constant in time or their change is negligible within the period they refer to. This hypothesis and the definition of $S_{\text{time}}|_{\text{clim}}$ together guarantee that there is no correlation in time between quantities referring to different temporal periods considered in the CCRA. Moreover, the reference period

Example

Suppose the system under study is the Eiffel Tower. The works started in 1887 and lasted two years, hence

$S_{\text{time}}|_{\text{clim}} = \{t : t \text{ day from 1st January 1851 to 31st December 1880}\}$

is chosen as reference period. Normals can be evaluated for the climate data referred to $S_{\text{time}}|_{\text{clim}}$ and data related to the system describe it as if it would not be affected by the passing of time.
If the period from 1st January 1861 to 31st December 1890 were chosen instead, no assessments could be produced for the years subsequent to the end of works.

In contrast to the reference period, averaging periods for future climate span 20 years and are fixed. Values referred to these periods describe the system or the climate at future time horizons, which is an useful information for any planning involving the system.[9, p. 23] The lower number of years in these periods do not affect negatively the prediction skill of statistics related to them.[1, p. 17] Three time horizons are chosen:

near from 1st January 2024 to 31st December 2043;

medium from 1st January 2044 to 31st December 2063;

long from 1st January 2081 to 31st December 2100.

Near and medium-term time horizons are chosen to be as close as possible to the present (at time of writing). This way it is more reasonable to find adaptation plans and strategies for the system at risk. Long-term time horizons are affected by greater uncertainty for different reasons, e.g. lower confidence on outputs from climate projections, exposure subject to change. Nevertheless, the long period is chosen to show differences between scenarios, which are more evident at the end of the century for many ECVs.

2.1.2 Reference dataset

The climate dataset used for evaluating reference values is ERA5 by European Centre for Medium-Range Weather Forecasts (ECMWF).[28] ERA5 is a reanalysis dataset, which provides gridded data with global coverage and hourly temporal resolution. Reanalyses are observations of climate data interpolated on a spatiotemporal grid throught numerical models, a procedure called data assimilation (see [29] for technical details). The main technical data about ERA5 can be found in table 2.1.

Table 2.1: Subset of the technical characteristics of ERA5, the complete list can be found in [29, p. 2003].

Characteristic	Value
Horizontal coverage	global
Horizontal resolution	$0.25° \times 0.25°$
Temporal coverage	from 1st January 1940 to present
Temporal resolution	hourly

In this work the ERA5 horizontal resolution of 0.25°, i.e. about 31 km, is used for both latitude and longitude. In the dataset, horizontal coordinates of a grid point natively refer to the upper left angle of the cell. A traslation is applied to refer these coordinated to the centre of the cell. A square box 3 grid cells wide and centered approximately in the coordinates of the system is chosen for each case study. The systems studied in this work has spatial scale much smaller than the size of a grid cell (see section ??), hence it is guaranteed that the central grid cell encompasses the systems, even if the coordinates of the centre of the system are not accurate. Although one grid cell is enough to cover the systems under study, an extended area is chosen to increase the predictive skill of aggregation procedures applied to the spatial dimensions. On the other hand, the CCRA would lose spatial accuracy in the description of the local events around the system, if too many grid cells are selected.

On the temporal dimension, climate data from 1st January 1950 to 31st December 2023 are selected from ERA5. First, data are converted to a calendar with 365 days by removing 29th February in leap years. Then they are downsampled to daily resolution with the same aggregation procedures specified by WMO for the evaluation of individual monthly values from daily values.[1, p. 5] In particular:

- daily Near-Surface Air Temperature is the mean of hourly Near-Surface Air Temperature of the same day;
- daily Maximum Near-Surface Air Temperature is the maximum of hourly Maximum Near-Surface Air Temperature of the same day;
- daily Minimum Near-Surface Air Temperature is the minimum of hourly Minimum Near-Surface Air Temperature of the same day;
- daily Precipitation is the sum of hourly Precipitation of the same day.

Timestamps for daily data are set at midnight.

2.1.3 Climate projection dataset

Future climate is studied using the NEX-GDDP-CMIP6 dataset provided by NASA Earth Exchange (NEX).[51, 52] The dataset is derived from results of Coupled Model Intercomparison Project Phase 6 (CMIP6) for a subset of ECVs and a single variant of 35 models from a selection of historical and ScenarioMIP experiments.[21]

Models are numerical representations of the climate and in general are called general circulation models (GCMs) or Earth system models (ESMs) when advanced processes of Earth are included (e.g. biological processes and feedbacks in EC-Earth3, see [17]). Models working at smaller scales are available: they can be used to dynamically downscale the projections, but they propagate existing systematic errors from the GCMs and introduce new ones. Methods to correct these errors are available but with the disadvantage to lose information on global processes given by GCMs and the physical interpretation of outputs.[18] Therefore only models at the global scale are used in this work.

The purpose of having a set of different models from NEX-GDDP-CMIP6 is to evaluate the uncertainty on predictions, in fact each model has different characteristics and applying ensemble methods reduces the variance on the outputs given by model-specific characteristics (e.g. different equations describing the same phenomena, different modules between models). NEX-GDDP-CMIP6 provides a single variant for each model. Data are obtained through statistical downscaling and bias adjustment procedures presented in [50]. The main technical data about NEX-GDDP-CMIP6 can be found in table 2.2, while the full description of the dataset is in [51].

Table 2.2: Subset of the technical characteristics of NEX-GDDP-CMIP6, see [51] for the full specifications.

Characteristic	Value
Horizontal coverage	global
Horizontal resolution	$0.25° \times 0.25°$
Temporal coverage	from 1st January 1950 to 31st December 2100
Temporal resolution	daily

The spatial resolution of this dataset matches the resolution of ERA5 and horizontal coordinates identify the centre of grid points, hence no further rescaling is required. Same spatial coordinates of the reference data are used.

Data of NEX-GDDP-CMIP6 have daily resolution but timestamps are referred to noon of the coordinate. This does not raise problems when operations are applied to data aggregate at lower frequencies, e.g. monthly averages, but may create contradictions in pointwise calculations. Therefore, timestamps in NEX-GDDP-CMIP6 are redefined to match the timestamps or ERA5, i.e. midnight. The temporal coverage is split between historical and future experiments. The historical simulation starts at 1st January 1950 and ends at 31st December 2014, while the projections are from 1st January 2015 to 31st December 2100.

In this work some models are excluded, reasons for exclusion are in appendix A.1 along with the list of used models. For each model, the following experiments are considered:

historical simulation of the past climate;

SSP1-2.6 low emission scenario, with low challenges in mitigation and adaptation to climate change;

SSP2-4.5 intermediate scenario, with moderate challenges;

SSP3-7.0 high emission scenario, with high challenges.

More details on the narratives of each Shared Socioeconomic Pathway (SSP) are found in [37]. The use of SSP scenarios allows to account for the evolution of socioeconomic elements which may affect indirectly the system. In each model the historical experiment is extended up to 31st December 2023 using data from the SSP2-4.5 experiment. This procedure is suggested by [21, p. 1954] and allows to compare historical data from models with the reference dataset, in what can be considered the *past* of the study, while the *future* starts at 1st January 2024.

Non-physical temperature extremes

At the time of writing, NEX-GDDP-CMIP6 dataset contains some values of Minimum Near-Surface Air Temperature and Maximum Near-Surface Air Temperature which are not accettable from a physical perspective, i.e. tasmin > tasmax, for the same days and some models.[3]

The issue appears as a rare by-product of the bias adjustment algorithm employed in the dataset creation, see [50]. It does not affect calculations on normals since they are monthly means, but for resolutions on the order of days may be conditioned negatively by the non-physical value. To be able to recover those data helps to maintain accurate information on the distribution of extremes and its evolution due to climate change, see [46, pp. 1536–1537] and [23, pp. 40–42].

From a discussion with the providers of the dataset, the suggested course of action is to swap tasmin and tasmax values for data presenting the problem.

2.1.4 Bias adjustment

Outputs of GCMs and the more advanced ESMs have intrinsic biases related to their functioning (e.g. implementation, physical equations, parametrisations) which need to be adjusted to convey physically accurate values, essential for studies like CCRAs.[4] A moltitude of BA methods are available, e.g. deviations from reference data, statistical analysis, ML models.[7, 39, 36]

When BA is performed on climate data, a reference is chosen. The reference data are assumed to be a representative sample of the population, hence the sample distribution of reference data describes the probability distribution of the climate data accurately. The BA procedure extracts information

[3]Also Near-Surface Air Temperature occurs to have non-physical values, i.e. tas < tasmin or tas > tasmax. However, this issue is not addressed explicitly, since every chosen indicator having temperature variables as inputs does not require tasmin or tasmax to be used together with tas.

[4]In many resources on the topic, the term *bias correction* is used instead. Here bias adjustment (BA) is preferred since a correction requires a true value as reference, which is not always possible to assume.

on statistics of reference data and modifies the climate data to reproduce those statistics. In fact, biases are considered alterations of the true probability distribution induced by the models and BA aims to remove them. Moreover, climate change affects the probability distributions making them non stationary. This means that statistical information in a given temporal period may not be accurate to describe data in future periods, even if they are extracted from the reference data. Some BA procedures address this issue.

In this study the BA algorithm known as Quantile Delta Mapping (QDM) is adopted.[7] It belongs to the family of Quantile Mapping (QM) algorithms for BA, which use statistical information from quantiles of reference data to remove the bias. QDM is able to preserve trends of climate change detected by the GCMs, by storing the difference by quantile of future periods with respect to an historical period. Depending on the climate data, the relative change may be stored instead of the absolute difference.

As explained in [7, pp. 6941–6942], QDM estimates three empirical quantile functions (QFs): one for the climate data to adjust, one for the reference data and one for the climate data in the same period of reference data. Then differences between same quantiles of climate data at different temporal periods are stored. The actual adjustment consists in replacing target climate data with the corresponding quantiles from the reference data and adding back the differences stored previously.

The mapping between the empirical QFs in the common period may be interpreted as the training step of the BA algorithm. Moreover, the procedure requires to invert the QFs, i.e. to evaluate the corresponding empirical cumulative distribution functions (CDFs) of data, to map quantiles to their probabilities.[5]

Concerning this study, the reference distribution is built on ERA5. The period from 1st January 1950 to 31st December 1993 is chosen to extract the information needed for BA. Then the 30-years period from 1st January 1994 to 31st December 2023 is used to test the accuracy of the BA procedure. The BA is applied to ECVs of each model in NEX-GDDP-CMIP6. A q-q plot is made to compare the adjusted data against the reference data.

Temperature

QDM is applied additively to temperature data. This means that to conserve trends between projections and historical data, the absolute difference between quantiles is stored.

Temperature data subject to adjustment are ECVs tas, tasmin and tasmax.

[5]More properly they are sample frequencies instead of probabilities, but for clarity the latter term is used.

In particular, first tasmax and the Diurnal Temperature Range

$$\mathrm{DTR} = \mathrm{tasmax} - \mathrm{tasmin} \tag{2.2}$$

are adjusted, then the adjusted tasmin is derived by inverting equation (2.2). This procedure is suggested in [50, p. 3313]. By definition DTR is always non negative, hence this procedure should ensure physical values for the extremes tasmin and tasmax.

Precipitation

For precipitation data, trends are preserved by storing the ratio of projected data with respect to historical data, i.e. multiplicative QDM is applied. The adjustment is applied to Precipitation pr. However, null values are present in the datasets, which correspond to days without any kind of precipitation, i.e. dry days. When they appear in the historical data, the trend-preserving ratio diverges to infinity, resulting in a non-physical infinite value of the adjusted pr.

The procedure suggested in [7, p. 6945] is followed to solve the issue: values lower than the threshold 0.05 mm/d are randomised uniformly in the interval $(0\,\mathrm{mm/d}, 0.05\,\mathrm{mm/d})$, then after the BA the values which are below the threshold are considered dry days, hence they are set to 0 mm/d. No correction in the seasonal cycle is applied since only daily data are needed for the evaluation of indicators.

2.2 Indicators

Indicators of drivers within the hazard determinant are functions of climate data and additional parameters. In this work the climate data are ECVs and they have a daily frequency. During their calculation, generally indicators are aggregated over the temporal dimension and are non-linear functions of their arguments. An indicator I can be defined mathematically as

$$I : S_{\mathrm{lat}} \times S_{\mathrm{lon}} \times S_{\mathrm{y}} \times \prod_{p \in P_I} S_p \to \mathbb{R} \tag{2.3}$$

where S_{y} is a set of the years considered during the analysis, P_I is the set of parameters for that indicator and S_p is the set of values available for each parameter $p \in P_I$.[6] In the following, $\underline{z} \in \prod_{p \in P_I} S_p$ represents the set of arguments passed to the indicator, in other words the coordinates of I as multidimensional array. Evaluation is performed for each year, i.e. the indicator has yearly resolution or is evaluated with yearly frequency. As a consequence, the elements of set S_{y} are references to the years taken into account during calculations.

[6] As a symbolic shortcut, if $P_I = \varnothing$ then the indicator is defined only over $S_{\mathrm{lat}} \times S_{\mathrm{lon}} \times S_{\mathrm{y}}$.

An indicator can be represented as a multidimensional array, similarly to ECVs. The dependence of an indicator on ECVs is not clear in the definition given by equation (2.3), but in the following this is made explicit by the context or by the definition of the indicator.

Example

The indicator $\mathrm{TX_x}$ is evaluated for the period 1991-2020 with yearly frequency. This indicator is the monthly maximum value of daily maximum temperature,[19] hence:

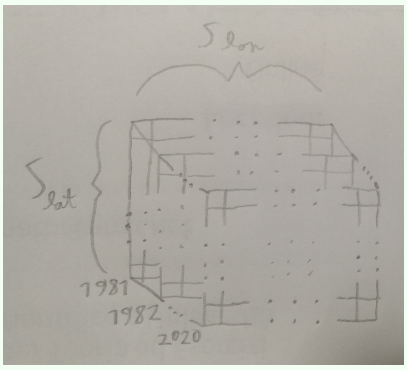
- it depends on ECV Maximum Near-Surface Air Temperature defined at daily frequency over the considered period,

$$S_{\text{time}} = \left\{ t : \begin{array}{l} t \text{ day from 1st January 1991} \\ \text{to 31st December 2020} \end{array} \right\} \quad ;$$

- spatial dimensions are not specified, hence the evaluation is performed for each point of an arbitrary set $S_{\text{lat}} \times S_{\text{lon}}$;
- no additional parameters are required, $P_{\mathrm{TX_x}} = \varnothing$;
- the outcome is a scalar value for each year in the period,

$$S_{\text{y}} = \{1991, 1992, \ldots, 2020\} \quad ;$$

- the multidimensional array representation of the indicator is in the following figure, where each entry is a real value with unit K:



Indicators of drivers within exposure and vulnerability determinants may be defined similarly as the hazard determinant as scalar functions depending on specific variables characterising the system.

2.3 Methodology of risk assessment

Restricting the risk assessment to climate-related applications is not sufficient to fix every detail, e.g. how to evaluate risk from its determinants. These implementation details are often expressed in the methodology chosen to perform the risk assessment. The methodology employed in this study is presented conceptually in these paragraphs and defined operatively in sections 2.3.1 and 2.3.2.

The methodology is split into eight modules, each dependent on the previous ones. The following is an overview:

1. understand the context in which the assessment is framed and identify objectives, scope and resources involved;[49, pp. 39–53]

2. identify risks and impacts affecting the system under study and determine drivers of hazard, exposure and vulnerability;[24, pp. 26–41]

3. choose indicators for each driver of hazard, exposure and vulnerability;[49, pp. 73–84]

4. collect data and quantify indicators;[49, pp. 87–103]

5. normalise indicators to allow their comparison;[49, pp. 105–119]

6. for each determinant, weight normalised indicators and aggregate them into a single value;[49, pp. 121–131]

7. aggregate values for individual determinants into a single value for risk;[49, pp. 133–141]

8. present the results of the CCRA.[49, pp. 143–154]

When the vulnerability of the system is recalled, it is split into sensitivity and adaptive capacity if possible.

All modules are connected by the concept of impact chain, which is an *analytical approach that enables understanding of how given hazards (3.8) generate direct and indirect impacts (3.14) which propagate through a system (3.3) at risk (3.13)*, from [31]. This concept helps to develop the CCRA as a narrative and to guide it smoothly through its various steps, see [32, pp. 217–224] for a review of the concept.

Although a complete application of this methodology does not fall into the purposes of the present study, each module is briefly addressed in section **??** where case studies are treated.

2.3.1 Evaluation of indicators

This section explains the process to obtain a scalar value for each determinant, following the methodology presented in section 2.3. Modules 3, 4, 5 and 6 are recalled. Suppose a set of drivers is chosen. The selection of drivers for the actual case studies, i.e. module 2, is performed and argued in section **??**.

Module 3 may be stated symbolically as follow. For each driver within the hazard determinant, a set $\mathcal{H}_j$ of indicators is obtained. A similar procedure is carried out for drivers of exposure and vulnerability, resulting in sets $\mathcal{E}_i$ and $\mathcal{V}_k$, respectively. Indices i, j and k are present to clarify that each set is related to a different driver and the way these sets are indexed is not important (e.g. each of them can be a sequence of integers where each one refers to a different driver, they can be the names of the drivers they refer to). If the distinction between drivers of sensitivity and adaptive capacity is made, then it is not explicit in the indices. The reason is that these drivers are treated mathematically the same way, as explained below.

Note that in module 3 no evaluation is performed yet, hence the elements of each set are just scalar functions. In other words, they are just descriptions of how they quantify the driver.

The methodology suggests to avoid double counting of drivers by allocating each of them in one determinant only.[24, p. 29] This implies to have different indicators, even if they are defined in a similar way.

Example

The risk of water scarcity affecting a location is assessed. This example is inspired by [24, p. 46]. The system is the location under study. One driver of exposure and two of vulnerability are chosen, they are respectively:

e1 presence of farmers in the region;

v1 insufficient know-how about irrigation systems;

v2 weak institutional setting for water management.

Both drivers of vulnerability describe the adaptive capacity of the system. All drivers are conveniently identified by lables.

An indicator for each driver is chosen, the resulting sets are:

$$\mathcal{E}_{\mathrm{e1}} = \left\{ \text{“number of farmers in the region”} \right\} ,$$
$$\mathcal{V}_{\mathrm{v1}} = \left\{ \text{“number of farmers trained in improved irrigation techniques”} \right\} ,$$
$$\mathcal{V}_{\mathrm{v2}} = \left\{ \text{“number of local water co-operations”} \right\} .$$

Note that all indicators consist in counting some elements of the system. Nevertheless, they are different from each other since they refer to different elements.

In module 4 the evaluation of indicators on climate and system data occurs. Concerning the system, the data collection step is explained in section **??** and scalar values are readily obtained for the elements in sets $\mathcal{E}_i$ and $\mathcal{V}_k$ for any driver i or k. See paragraphs about data in section **??** for the definition of the indicators of exposure and vulnerability used to describe each system.

A more convoluted path is needed to evaluate indicators of hazard. They are functions defined by equation (2.3), hence they depend on climate data and additional parameters. The former are presented in section 2.1, the latter are chosen as explained in the following paragraphs.

For each indicator, a set of values of its parameters is defined. Ideally these sets would be continuous, to explore the whole space of possible configurations of parameters. However, for limitations intrinsic to the analysis tools, only a finite and small number of values can be considered (in the following these discrete sets are called intervals to preserve generality). How values in these intervals are selected depends on the nature of the parameters. The selection is ultimately arbitrary, to allow greater control, e.g. remove values which are not interesting for the analysis, and to apply a form of non-parametric sampling of the input space. This is a form of space-filling design for SA.[15, pp. 593–594]

To simplify the explanation, consider driver j and an indicator $I \in \mathcal{H}_j$. This indicator depends on some parameters, which are collected in set P_I, and on some ECVs. The chosen interval for a parameter $p \in P_I$ is a set of scalar values, possibly with units, denoted by S_p.

If parameter p is related to a ECV (e.g. threshold on tas), its values are sampled from the distribution of the ECV. First all data available for the ECV of interest are collected in a single sample, with the following conditions:

- temporal coordinates belong to the averaging period S_{clim} chosen for the normals;

- spatial coordinates are ignored.

This procedure has the side effects of removing the dependence of parameter values from spatial and temporal coordinates and to increase the sample size. The sampling is not affected by existing spatial correlation between data, because it is non parametric and regards only the possible values of the ECV and not their spatial distribution. In fact, the probability of having any value v for the ECV T in the sample is

$$\mathcal{P}(v) = \frac{1}{|S_{\text{lat}}||S_{\text{lon}}||S_{\text{clim}}|} \sum_{y \in S_{\text{lat}}} \sum_{x \in S_{\text{lon}}} \sum_{t \in S_{\text{clim}}} \mathbb{I}[T(y,x,t) = v] \tag{2.4}$$

This is a frequentist probability and gets more accurate the larger the sample size is, by definition. Second, the empirical QF of data is built from the sample, to acknowledge the shape of their true probability distribution. Minimum and maximum values are treated as the first and last quantiles, respectively. Since the number of data is large but limited, this curve is an approximation of the inverse function of the CDF and missing data are interpolated linearly. Third, values are chosen with the aim to sample the true probability distribution uniformly. The density of points may be increased where needed to have a better description of the shape of the distribution.[7]

If parameter p is not related to a ECV (e.g. window size for moving averages), some heuristic is applied and explained case by case where values are presented in section **??**.

After S_p is defined for every $p \in P_I$, the indicator I is finally evaluated. This results in elements of set $\mathcal{H}_j$ being multidimensional arrays given by equation (2.3), for every driver j of the hazard. Different indicators may have different parameters, but they depend on ECVs which same spatial and temporal coordinates $S_{\text{lat}} \times S_{\text{lon}} \times S_{\text{clim}}$, hence they have same temporal frequency, i.e. same S_{y}.

These results need further elaboration. In fact, for every driver i and k, $\mathcal{E}_i$ and $\mathcal{V}_k$ contain scalar values which encapsulate information about the system for the chosen time period and system without reference to spatial coordinates. To obtain an analogous result for drivers of hazard, indicators are aggregated over spatial and temporal dimensions. For simplicity intermediate results are identified with the same variable I. First, the temporal aggregation is performed. It consists in averaging the multidimensional array over the temporal dimension with a sample average. The outcome is

[7] Why do not use derivative-based methods to set the density of points? The reason is again greater control on the selected values: there is no need to evaluate the derivative of the QF in every point, just within the subintervals which are interesting for the analysis. Note that the QF is obtained by linear interpolation between existent data values, hence the slope is already evaluated internally and the derivative is a piecewise constant function.

multidimensional arrays depending on spatial coordinates and parameters:

$$I(y, x, t, \underline{z}) \mapsto I(y, x, \underline{z}) = \frac{1}{|S_{\mathrm{y}}|} \sum_{t \in S_{\mathrm{y}}} I(y, x, t, \underline{z}) \quad . \tag{2.5}$$

Due to the spatial resolution of data, they may contain bias with respect to the reference period, e.g. orography may influence differently the variation of some ECVs. Therefore, for every indicators I, its relative variation with respect to the reference period is used,

$$I(y, x, \underline{z}) \mapsto I(y, x, \underline{z}) = \frac{I(y, x, \underline{z}) - I_{\mathrm{clim}}(y, x, \underline{z})}{I_{\mathrm{clim}}(y, x, \underline{z})} \quad , \tag{2.6}$$

where symbol I_{clim} is used to refer to I evaluated for the reference period, i.e. equation (2.5) with $S_{\mathrm{y}} = S_{\mathrm{clim}}$. This is analogous to evaluate anomalies for indicators instead of ECVs and rescale them on the respective value of the reference period. Then, the spatial aggregation is performed by using empirical orthogonal function (EOF) analysis as a dimensionality reduction technique.[8] The following procedure is applied to every indicator I in its multidimensional array representation:

1. assign $S_{\mathrm{lat}} \times S_{\mathrm{lon}}$ as the feature dimension of the design matrix;
2. assign $\prod_{p \in P_I} S_p$ as the sample dimension of the design matrix;
3. apply the EOF analysis to the design matrix;
4. keep the first PC only, i.e. the coefficients corresponding to the EOF which maximises the variance in the sample dimension.

In point 2 of the procedure, a bijective relations between the sample dimension of the design matrix and $\prod_{p \in P_I} S_p$ is established, hence the first PC effectively maps I to a multidimensional array with coordinates in $\prod_{p \in P_I} S_p$:

$$I(y, x, \underline{z}) \mapsto I(\underline{z}) \quad . \tag{2.7}$$

After the spatial and temporal aggregations, for every driver j each element $I \in \mathcal{H}_j$ depends only on parameter values in $\prod_{p \in P_I} S_p$.

To execute module 5, first the scale of each indicator is defined. In this work all indicators are numeric values and may have both metric or categorical scales (i.e. values are distributed uniformly or not, respectively, cf. [49, p. 109]). When metric scales are involved, the methodology suggests

[8] Terminology is varied. Here the eigenvectors, i.e. spatial patterns, are referred to as EOFs and their coefficients, i.e. temporal patterns, are the principal components (PCs). The object containig data is called design matrix with samples, i.e. observations, organised in rows and their features, i.e. variables which describe them, in columns. For further clarification on the terminology see [54, pp. 626–627] and for a recap on EOF analysis see [35, pp. 6502–6503] and [27, pp. 1121–1122].

to apply the min-max normalisation. Instead, in the present work indicators which are scalar values are not transformed,[9] while indicators which depend on parameters are standardised, i.e. substituted by their z-score. More in detail, for any indicator I undergoing normalisation, the new value is

$$I(\underline{z}) \mapsto I(\underline{z}) = \frac{I(\underline{z}) - \mu_I}{\sigma_I} \tag{2.8}$$

where the sample mean

$$\mu_I = \frac{1}{\prod_{p \in P_I} |S_p|} \sum_{\underline{z} \in \prod_{p \in P_I} S_p} I_{\text{clim}}(\underline{z}) \tag{2.9}$$

and the sample standard deviation

$$\sigma_I = \sqrt{\frac{1}{\prod_{p \in P_I} |S_p| - 1} \sum_{\underline{z} \in \prod_{p \in P_I} S_p} \big(I_{\text{clim}}(\underline{z}) - \mu_I\big)^2} \tag{2.10}$$

are calculated using values obtained for the reference period S_{clim}.[38, p. 84] The advantage of equation (2.8) with respect to min-max normalisation is to be flexible when new values are introduced, in fact they are measured in terms of statistics of the reference period without breaking the normalisation.[10] To normalise categorical scales, the methodology suggests first to group the values in five classes, then replace them with specific values in the range $[0, 1]$, see [49, pp. 115–116]. Higher normalised values are associated to more negative impacts. However, this case does not occur in the present study since every indicator with categorical scale is a constant value. Not normalising some indicators may seem wrong since normalisation is a requisite to compare them, but the reason is supported mathematically in the next paragraphs.

For module 6, the weight w_I of each indicator I is set to 1, because no particular influence on the final risk is known a priori. Since indicators are unique, there is not ambiguity to identify their weights with their names as labels. This choice of weighting has not effects on the final risk value, as explained in section 2.3.2. Then, for each determinant the weighted mean of its indicators is computed. Since all indicators are weighted equally, the result equals the arithmetic mean. In [24, p. 51] this process is represented graphically with a single indicator for each driver. The results are a scalar value for exposure

$$E = \frac{1}{\sum_i \sum_{I \in \mathcal{E}_i} w_I} \sum_i \sum_{I \in \mathcal{E}_i} w_I I \quad , \tag{2.11}$$

[9] Formally they are divided by a unit value of their quantity to obtain dimensionless values, which are trivially compatible and easily used as arguments in mathematical functions. Note that this is not necessary for hazard indicators because of the procedure to remove bias from climatology.

[10] See section B.1 for further insight on why min-max normalisation is not used.

a scalar value for vulnerability

$$V = \frac{1}{\sum_k \sum_{I \in \mathcal{V}_k} w_I} \sum_k \sum_{I \in \mathcal{V}_k} w_I I \tag{2.12}$$

and a scalar function for hazard $H : \prod_j \prod_{I \in \mathcal{H}_j} \prod_{p \in P_I} S_p \to \mathbb{R}$, which depends on all parameters, defined as

$$H(\underline{z}) = \frac{1}{\sum_j \sum_{I \in \mathcal{H}_j} w_I} \sum_j \sum_{I \in \mathcal{H}_j} w_I I(\underline{z}_I) \tag{2.13}$$

where $\underline{z}_I \in \prod_{p \in P_I} S_p$ is the sequence of values for parameters which are arguments of I. Note that the there is no need to treat drivers of adaptive capacity and sensitivity separately because the aggregation procedure is applied equally to them.

Note that in module 6 a relation between indicators within the same determinant is established through the aggregation procedure, hence the results may be regarded as category 1 complex hazards. Moreover, the concept of intermediate impact, which mediates drivers of hazard and vulnerability, are a form of category 2 complex hazard.[24, p. 33]

2.3.2 Evaluation of risk

Scalar values representing each determinant of risk are aggregated into a single value. The aggregation procedure is a weighted mean, see module 7, and the weights assigned to each determinant are $w_E = 1$, $w_H = 1$ and $w_V = 1$. Then, analogously to the aggregation of hazard indicators in equation 2.13, the value for risk is a scalar function $R : \prod_j \prod_{I \in \mathcal{H}_j} \prod_{p \in P_I} S_p \to \mathbb{R}$ which depends on all parameters:

$$R(\underline{z}) = \frac{w_E E + w_H H(\underline{z}) + w_V V}{w_E + w_H + w_V} \quad . \tag{2.14}$$

The risk value is a linear function of normalised hazard indicators. This can be seen easily by manipulating equation (2.14),

$$R(\underline{z}) = c_0 + \frac{w_H H(\underline{z})}{w_E + w_H + w_V} = c_0 + c_1 \sum_j \sum_{I \in \mathcal{H}_j} w_I I(\underline{z}_I) \tag{2.15}$$

with $c_0 = \frac{w_E E + w_V V}{w_E + w_H + w_V}$ and $c_1 = \frac{w_H}{(w_E + w_H + w_V) \sum_j \sum_{I \in \mathcal{H}_j} w_I}$, and it holds true as long as the aggregation procedures for risk and hazard are linear.

One of the problems which justifies this work can be stated using equation (2.14): given different choices of indicators or parameters, the resulting risk value can be the same, as long as the differences in values balance out.

Example

Risk is assessed for a system, E and V are known and only one driver of hazard is considered. Two sets of different indicators are prepared, $\mathcal{H}'$ and $\mathcal{H}''$, functions may differ only in the values of their parameters.These alternatives would be equivalent to describe the driver mathematically from different points of view.
Even if all indicators have different values after the calculation steps, the aggregated values of hazard H' and H'' for sets $\mathcal{H}'$ and $\mathcal{H}''$, respectively, are ideally equal. The same same risk value R results from the aggregation, since E and V do not depend on the choices regarding the hazard. This is the expected outcome, because changing the mathematical description of the physical phenomenon should not change the final risk.

A final non-linear transformation is performed on risk value R, to simplify the presentation and comparison of risk values. Values obtained from all the combinations of parameters are classified accordingly to five categories, in increasing order of severity:[24, p. 53]

1. very low;
2. low;
3. intermediate;
4. high;
5. very high.

This transformation can be formalised as a piecewise function $r : \prod_j \prod_{I \in \mathcal{H}_j} \prod_{p \in P_I} S_p \to \{\text{very low}, \text{low}, \text{intermediate}, \text{high}, \text{very high}\}$, where the thresholds for each piece are the quantiles of the image of $\prod_j \prod_{I \in \mathcal{H}_j} \prod_{p \in P_I} S_p$ through function R for the reference period:

$$r(\underline{z}) = \begin{cases} \text{very low} & R(\underline{z}) < q_1 \\ \text{low} & q_1 \leq R(\underline{z}) < q_2 \\ \text{intermediate} & q_2 \leq R(\underline{z}) < q_3 \\ \text{high} & q_3 \leq R(\underline{z}) < q_4 \\ \text{very high} & R(\underline{z}) \geq q_4 \end{cases} . \tag{2.16}$$

Thresholds q_1, q_2, q_3 and q_4 are calculated from risk values of the reference period because hazard drivers are supposed to change risk and impacts with time. Moreover, the pieces of the function reflect the fact that the image of R is not bounded, due to the aggregated values of determinants being not bounded by the chosen normalisation. This allows to account for extreme values of risk in periods different from the reference.

Module 7 addresses the possible aggregation of multiple sub-risks into an overall risk value.[24, p. 54] According to section 1.1.2, the outcome would be a complex risk belonging to category 3. This additional elaboration is not implemented in the present work because an individual risk is studied, i.e. the climate risk.

Appendix A

Additional implementation details

A.1 Selection of CMIP6 models

Some models available in NEX-GDDP-CMIP6 are excluded from the present study because they present issues which can not be contained without affecting the calculations. Table A.1 list both the used models and the excluded models, along with additional information.

The most frequent issue is the lack of data for some of the used ECVs or for some SSPs. On the contrary, model GISS-E2-1-G occasionally presents multiple values for the same day, hence to avoid introducing systematic errors on which values should be considered or how to aggregate them, the model is excluded from the list.

Finally, two models have temporal coordinates set on a different calendar than the one used in this work, namely a 360-day calendar. Calendars are defined by the Model Intercomparison Project (MIP) endorsed GCMs but no restriction is imposed on the possibility to convert from one to another.

Table A.1: Models available in NEX-GDDP-CMIP6. The part of the table above the line shows the models used in the present study, their CMIP6 variant is specified. Below the line the models which are excluded are listed, along with the reason for their exclusion.

Model	Notes
ACCESS-CM2	Variant r1i1p1f1
ACCESS-ESM1-5	Variant r1i1p1f1
BCC-CSM2-MR	Variant r1i1p1f1
CanESM5	Variant r1i1p1f1
CMCC-ESM2	Variant r1i1p1f1
CNRM-CM6-1	Variant r1i1p1f2
CNRM-ESM2-1	Variant r1i1p1f2
EC-Earth3	Variant r1i1p1f1
EC-Earth3-Veg-LR	Variant r1i1p1f1
FGOALS-g3	Variant r3i1p1f1
GFDL-ESM4	Variant r1i1p1f1
INM-CM4-8	Variant r1i1p1f1
INM-CM5-0	Variant r1i1p1f1
IPSL-CM6A-LR	Variant r1i1p1f1
MIROC-ES2L	Variant r1i1p1f2
MIROC6	Variant r1i1p1f1
MPI-ESM1-2-HR	Variant r1i1p1f1
MPI-ESM1-2-LR	Variant r1i1p1f1
MRI-ESM2-0	Variant r1i1p1f1
NorESM2-LM	Variant r1i1p1f1
NorESM2-MM	Variant r1i1p1f1
TaiESM1	Variant r1i1p1f1
CESM2	Missing data
CESM2-WACCM	Missing data
CMCC-CM2-SR5	Missing data
GFDL-CM4	Missing data
GFDL-CM4_gr2	Missing data
GISS-E2-1-G	Data with sub-daily resolution
HadGEM3-GC31-LL	Missing data
HadGEM3-GC31-MM	Missing data
IITM-ESM	Missing data
KACE-1-0-G	Calendar of 360 days
KIOST-ESM	Missing data
NESM3	Missing data
UKESM1-0-LL	Calendar of 360 days

Appendix B

Mathematical considerations

B.1 Min-max normalisation

When min-max normalisation is applied to a given indicator, it is rescaled to the $[0, 1]$ interval, with higher values associated to more negative impacts. If multiple temporal periods are involved, one is chosen as reference for the extreme values.[38, p. 85]

There is the implicit assumption is that the image of the indicator is bounded and its extremes are known. This is not always true, hence the extremes must be set in alternative ways (e.g. by discussing with experts, by consulting the literature, by analysing the system), see [49, pp. 113–115].

Once the extremes are found, the min-max normalisation of an indicator can be evaluated easily. Denote its image as $X \subset \mathbb{R}$ and the extremes as $x_{\text{max}} = \max X$ and $x_{\text{min}} = \min X$. Then the min-max normalisation applied to $x \in X$ is

$$\frac{x - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}} \quad . \tag{B.1}$$

In literature the min-max normalisation is frequently applied as suggested by the methodology (cf. [12, p. 6], [13, p. 6] and [25, p. 74]). In the present work it is not chosen because of two downsides:

1. The methodology is applied to a single system and the ranges of indicators are not known. This means that a single value representing the system exists for any given indicator and trivially it corresponds to its minimum and maximum values, making the outcome of the normalisation undefined. In literature this problem is avoided by considering a set of systems, which results in an ensemble of values for each indicator which is assumed to be its image.

2. In periods different from the reference there may be values of the indicator which exceed the extremes. They result in normalised values

which fall outside the interval $[0,1]$, invalidating the purpose of the normalisation. In literature this is issue is solved by clipping the exceeding values to the corresponding extremes of the interval.

B.2 Alternative aggregation for risk

Some methodologies suggest to evaluate risk as product of the aggregated values of exposure, hazard and vulnerability:

$$R = E\,H\,V \quad . \tag{B.2}$$

This procedure is used in contexts preceding the concept of risk introduced in [23] and it is still used in later articles (see [12, p. 7] and [13, p. 6]).

This procedure is used because it admits a null risk value, i.e. negligible impacts, when either of the values for its determinant is null. This reasoning is intuitive, but hides the request that values for determinants have exactly value zero when their impacts are negligible or balance out, which depends on the aggregation procedure used to evaluate them from their indicators. Moreover, it neglects the possibility to weight each determinant differently.

With respect to how risk is evaluated in the present work (see section 2.3.2 and equation (B.2)), two considerations can be made on this procedure. First, it is possible to rewrite equation (2.14) as equation (B.2) through a continuous transformation,

$$\begin{aligned} R'(\underline{z}) &= \exp\big(R(\underline{z})\big) = \\ &= \exp\left(\frac{w_E E}{w_E + w_H + w_V}\right) \exp\left(\frac{w_H H(\underline{z})}{w_E + w_H + w_V}\right) \exp\left(\frac{w_V V}{w_E + w_H + w_V}\right) = \\ &= E'\,H'(\underline{z})\,V' \quad . \end{aligned} \tag{B.3}$$

This allows to apply the considerations of the present study to CCRAs which evaluate risk as in equation (B.2). Note that an exact value of $R'(\underline{z}) = 0$ can not be obtained if real data and functions are used in the methodology. Second, in equation (B.2) R is linear with respect to H. As a consequence, if equation (B.2) is used instead of equation (2.14) and every other detail of the methodology follows section 2.3.2, then the risk value R is still a linear function of normalised hazard indicators:

$$R(\underline{z}) = E\,V \sum_j \sum_{I\in\mathcal{H}_j} w_I I(\underline{z}_I) \quad . \tag{B.4}$$

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Definitions

adaptation *process of adjustment to actual or expected climate (3.4) and its effects*, from [31]. 4

adaptive capacity *ability of systems (3.3), institutions, humans, and other organisms to adjust to potential damage, to take advantage of opportunities, or to respond to consequences*, from [31]. 4

anomaly *The deviation of a variable from its value averaged over a reference period.*, from [34, p. 2218]. 11

average *the mean of monthly values of climatological data over any specified period of time (not necessarily starting in a year ending with the digit 1). In some sources, this is also referred to as* provisional normal, from [1, p. 2]. 11

climate service *Climate services involve the provision of climate information in such a way as to assist decision-making. The service includes appropriate engagement from users and providers, is based on scientifically credible information and expertise, has an effective access mechanism and responds to user needs*, from [34, p. 2223] and [30, p. 831]. 2

climatological standard normal *averages of climatological data computed for the following consecutive periods of 30 years: 1 January 1981-31 December 2010, 1 January 1991-31 December 2020, and so forth*, from [1, p. 2]. *see* average

data assimilation *Mathematical method used to combine different sources of information in order to produce the best possible estimate of the state of a system. This information usually consists of observations of the system and a numerical model of the system evolution. Data assimilation techniques are used to create initial conditions for weather forecast models and to construct reanalyses describing the trajectory of the climate system over the time period covered by the observations.*, from [34, p. 2225]. *see* reanalysis, 12

determinant any component of risk, i.e. hazard, exposure, vulnerability, response, from [47, p. 493]. 3

driver individual component of a determinant, from [47, p. 493]. *see* determinant, hazard, vulnerability, exposure & response, 4

drought *An exceptional period of water shortage for existing ecosystems and the human population (due to low rainfall, high temperature, and/or wind)*, from [34, p. 2226]. 5

exposure *presence of people, livelihoods, species or ecosystems, environmental functions, services, resources, infrastructure, or economic, social or cultural assets in places and settings that could be affected*, from [31]. 3

hazard *potential source of harm*, from [31]. 3

impact *effect on natural and human systems (3.3)*, from [31]. 3

impact chain *analytical approach that enables understanding of how given hazards (3.8) generate direct and indirect impacts (3.14) which propagate through a system (3.3) at risk (3.13)*, from [31]. *see* hazard, impact & risk, 19

indicator *quantitative, qualitative or binary variable that can be measured or described, in response to a defined criterion*, from [31]. 4

maladaptation *Actions that may lead to increased risk of adverse climate-related outcomes, including via increased greenhouse gas (GHG) emissions, increased vulnerability to climate change, or diminished welfare, now or in the future. Maladaptation is usually an unintended consequence.*, from [34, p. 2238]. 6

normal *period averages computed for a uniform and relatively long period comprising at least three consecutive ten-year periods*, from [1, p. 2]. *see* period average, 9

period average *averages of climatological data computed for any period of at least ten years starting on 1 January of a year ending with the digit 1*, from [1, p. 2]. *see* average, 11

reanalysis *Reanalyses are created by processing past meteorological or oceanographic data using fixed state-of-the-art weather forecasting or ocean circulation models with data assimilation techniques. They are used to* *provide estimates of variables such as historical atmospheric temperature and wind or oceanographic temperature and currents, and other quantities. Using fixed data assimilation avoids effects from the changing analysis system that occur in operational analyses. Although continuity is improved, global reanalyses still suffer from changing coverage and biases in the observing systems.*, from [34, p. 2245]. *see* data assimilation, 12

response action enact to mitigate the effects of climate change or adapt to it. 3

risk *effect of uncertainty*, from [31]. 1

risk management *coordinated activities to direct and control an organization with regard to risk (3.1)*, from [3]. *see* risk assessment, 1

risk assessment *The qualitative and/or quantitative scientific estimation of risks.*, from [34, p. 2246]. *see* risk management, 1

sensitivity *degree to which a system (3.3) or species is affected, either adversely or beneficially, by climate (3.4) variability or change*, from [31]. 4

vulnerability *propensity or predisposition to be adversely affected*, from [31]. *see* sensitivity & adaptive capacity, 3

Acronyms

AR6 Sixth Assessment Report.

BA bias adjustment.

CCRA climate change risk assessment.

CDF cumulative distribution function.

CID climatic impact-driver.

CMIP6 Coupled Model Intercomparison Project Phase 6.

DRR disaster risk reduction.

ECMWF European Centre for Medium-Range Weather Forecasts.

ECV essential climate variable.

EOF empirical orthogonal function.

ESM Earth system model.

GCM general circulation model.

IPCC Intergovernmental Panel on Climate Change.

ISO International Organization for Standardization.

MIP Model Intercomparison Project.

ML Machine Learning.

NEX NASA Earth Exchange.

PC principal component.

QDM Quantile Delta Mapping.

QF quantile function.

QM Quantile Mapping.

SA sensitivity analysis.

SSP Shared Socioeconomic Pathway.

UA uncertainty analysis.

WMO World Meteorological Organization.

Symbols

$\diamondsuit$ placeholder for arbitrary argument or mathematical object.

$|\diamondsuit|$ absolute value or, if the argument is a set, cardinality.

$\diamondsuit|_{\mathbf{clim}}$ relate the argument to the reference period.

$\mathbb{I}[\diamondsuit]$ symbolic representation of a conditional test: returns 1 if the condition in square brackets is satisfied, else 0 (i.e. generalisation of a characteristic function of the argument in square brackets).

DTR Diurnal Temperature Range.

tasmax Maximum Near-Surface Air Temperature.

tasmin Minimum Near-Surface Air Temperature.

tas Near-Surface Air Temperature.

pr Precipitation.